A CONTENT BASED AND COLLABORATIVE FILTERING RECOMMENDER SYSTEM

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Abstract:

This research proposes a new recommendation system for recommendation generation based on users' ratings and personal profiles. Motivated by existing studies, firstly we propose item-based collaborative filtering to recommend tourist spots based on users' rating. In addition, we incorporate the content-based filtering algorithm with Naïve Bayes Classifier, for recommendation generation. Detailed analysis of these proposed methods are discussed which will give a clear view on how the core part of the recommendation systems has been implemented. The proposed TRS was evaluated using several data sets to indicate its efficiency.

Keywords:

Collaborative filtering; Content-based filtering; Naïve Bayes classifier; Recommendation system; Ratings and personalized profile

1. INTRODUCTION

Contribution of the tourism sector to the world economy is immense [1, 2] with a growing revenue over decades. It is very evident that internet is considered the main platform for the tourists to collect and view information on tourist spots. However, the volume of information is significantly high which disrupts the focus of the tourist process information and mostly all the websites does not provide a profile of a user, therefore the tourist spots that are being suggested will be the same as those of other users. In other words, it is not personalized.

The research aims to develop two recommendation systems for tourist spot suggestion. The first method is developed based on item-based Collaborative Filtering (CF) to recommend the top three tourist destination spots according to the previous users' rating. The second method will use Content-based Filtering (CBF) combined with naïve Bayes classifier (NBC). New users will be required to fill in their online profiles which will consist of two categories i.e. 'Interest' in general and 'Food & Drinks' to identify their preferences to provide the best possible suggestions based on the respective user profiles. A questionnaire is also used under profile section and is considered as a significant element in the system as it enables the system to collect the users' interests and preferences. Therefore, the Tourist Recommendation System (TRS) basically suggests tourist spots to the users based on two above methods, i.e. the collaborative filtering and content-based filtering integrated with NBC.

The rest of the paper is presented as follows. Section 2 discusses advantages and disadvantages of Content-based Filtering and Collaborative Filtering, choosing between User-based Collaborative Filtering and Item-based Collaborative filtering. And, NBC-based prediction is also introduced. Section 3 defines the research methodology and justifies why CF and CBF have been implemented in this research. Then, it defines resources and tools that have been used to develop tourist suggestion system. Section 4 presents the testing and results of the two proposed recommendation techniques and analyses their performances. Then, Section 5 concludes this research and discusses future directions which will help to further improve the proposed models.

2. LITERATURE REVIEW

With the ever-increasing usage of information technology comprising demanding users, many measures are taken to facilitate the users with an effective and efficient platform to provide a richer experience rather than typically providing a conventional static experience. The recommendation system is able to enhance user experience by analyzing users' behaviours and preferences and make corresponding suggestions in accordance to such inputs [3]. For instance, the recommendation system which communicates with users on what items can be purchased, what items can be considered next, what other relevant items can be purchased after a recent purchase etc. aids and facilitates the decision-making process of respective users. This is done through a thorough analysis of a user's past and recent purchases, searches and the degree of behavior similarity of the respective user with other users. There are two types of recommendation technique that would be able to implement, i.e. CF and CBF. In particular, with respect to CF, there are two types of methods, i.e. user and item-based filtering.

2.1. User-based Collaborative Filtering and Item-Based Collaborative Filtering

The user-based filtering compares a user with other users who have similar preferences based on the identical items ratings they have provided. This approach identifies the products that are preferred by the other users and then suggests those products to the user involved who is assumed to have similar preferences as those of the other users. The Pearson Correlation algorithm will be applied in this approach [4].

On the other hand, rather than matching the user to similar clients/customers as in the user-based collaborative filtering, in item-based filtering, the set of items would be rated based on the rating to similar items then all the items with similar rating and would be ranked. [5]. Therefore, the adjust cosine algorithm would be implemented for this approach.

2.2. A Machine Learning Method – Naïve Bayes Classifier

The NBC classifier is a popular machine learning method. The probability theory is the main concept behind NBC to ensure data classification. According to [6], The key value of using NBC is that the flexibility it gives to the prediction of an event once new data is introduced. The word naïve has been derived because of the assumption that it makes that all the features/attributes for decision making will be independent of each other. Such independence as well as a large training set increases the efficiency of NBC [7]. Therefore, the more the data it gets, the more accurate the model becomes.

3. THE PROPOSED RECOMMENDATION SYSTEM

3.1. User Rating Using CF

According to [9], the key function of CF is to perform in domains even when there is no much content related to the respective item. In other words, the content or information is insufficient to be analysed by a computer system. In fact, CF has a major ability which stands out from other methods or techniques, i.e. it is able to provide serendipitous recommendations. It means it can suggest items which are relevant to the respective user without using the data or information from the user's profile. Based on this, we decided to incorporate CF into our system. Since rating in the system would not have any text information or content, it will be only ratings from many other users. Hence, CF has been used to implement the rating recommendation part into the tourist suggestion system.

3.2. Content Based Filtering for User Profiling

As suggested by [9], CBF is distinctively different from CF. CBF is able to recommend items without ratings provided by users. This indicates that CBF will recommend items solely based on the user's profile. Moreover, the accuracy of the recommendation will not be affected even the database does not consist of the details of the user preferences. All it does is to extract the data from the user's profile and suggest based on that. According to [10], if users change their preference in their user profile, CBF would be able to adapt to the changes made and not only that, it would also be able to recommend in a short span of period. CBF can handle situations like even if the items are not shared commonly by the users, but only through identical items it still would be able to recommend based on their fundamental or core features. From the security aspect, CBF can be helpful to the users since users do not have to publish or share their user profile to get recommendations which ensures the privacy of the respective users. In tourist suggestion system, CBF played a vital role to make recommendations based on the user profile which may consist of all the user preferences with respect to tourist spots.

3.3. Data Collection and Analysis

For collaborative filtering recommendation system, it was more towards collecting the rating from a user and then it will be stored into the database to be used to recommend the tourist spots based on the previous ratings. Therefore, other users' rating really matters in recommending the attractions.

Furthermore, the idea behind the content-based recommendation system is to recommend attractions to users. The data needed for training have to represent what real world character profiles would be like. People typically have likes, dislikes, interests and hobbies which would affect their decision making. Since we employ a naive Bayes Classifier for such predictions, the training data need to be kept simple and mostly use binary data, so they either like or do not like an item; even the gender of the person is binary as male or female. There is one exception with respect to the desired price range with multiple value settings provided.

Due to the lack of online training data samples, the training has been mocked to allow the project to be a proof of concept. If the application goes in to production, additional functionality would need to be developed to allow the system to capture new records and add them to the training data. This would also allow the application to learn and collect more data as the system is deployed. Now this does raise an ethical problem as the website does record character profiles and does process the data, users would have to be informed of how the site collects it is data and what the data is used for. On the positive side the training data are anonymous, it simply indicates a person with certain likes and a profile on the visiting of an attraction. This method however does open the application to another issue which is the fact a company or user can forge visits to get an attraction to have a higher rating than others.

We now introduce how NBC is implemented and combined into TRS. Firstly, all the training data are loaded from the database, from which all the unique attraction IDs are extracted. The application then takes the personal profile of the user and iterates through both the unique attraction IDs and training data. If training sample's attraction ID matches the unique ID then the attraction sample number is incremented by one. Following this, if the attraction IDs match the application, then it iterates through the interests and likes of both the sample and the user personal profile looking for any other matches; any interest/like that matches the number, the match count for that interest/like is incremented by one. In summary, the application has a list of numbers which represent each profile interest and how many instances of the samples matched the user personal profile. Bayes theorem is used as the foundation for NBC for recommendation prediction.

One of the advantages of using Naïve Bayes Classifier for this project is to produce multiple predictions [11]. This is through the end results being a list probability which we can understand, order and manipulate to get more than one useful result.

3.4. Collobrative Filtering

Item based filtering, (also named as model-based collaborative filtering) does not have to store all the ratings. Therefore, it builds a model representing *how close* every attraction is to every other attraction.

To compute the similarity between attractions, a cosine similarity formula is implemented as follows.

$$sim(i,j) = \frac{\sum_{u\in U}(R_{u,i}-R'_u)(R_{u,j}-R'_u)}{\sqrt{\sum_{u\in U}(R_{u,i}-R'_u)^2}\sqrt{\sum_{u\in U}(R_{u,j}-R'_u)^2}} \quad (1)$$

By implementing this formula, it would be able to display the computed similarity values of ratings between the users. In in this particular formula $(R_{u,i} - R'_u)$, rating R, user u gives to attraction/item i deducts the average rating that given by the user to all the rated attractions.

$$P_{u,i} = \frac{\sum_{all\ similar\ items,N}(s_{i,N} \times R_{u,N})}{\sum_{all\ similar\ items,N}(|s_{i,N}|)} \quad (2)$$

Equation (2) is used to predict ratings of the not rated attractions.

3.5. Content Based Filtering

The reasoning behind the contingency is that in the real world it is highly unlikely to have a probably of zero. Calculation of the attraction probabilities is defined in the following equation [11]:

$$Attraction\ probability = (IP1 + IP2 \ldots + IPn) \quad (3)$$

where IP is the instance probability of each feature, and where n is the number of features. The instance probability (IP) is calculated by the following formula:

$$IP\ (c, x) = \frac{(prior \times likelihood)}{evidence} \quad (4)$$

where c is the target class (the attraction), and x represents the feature. Prior is calculated by the following:

$$prior\ (c, x) = xi + m \quad (5)$$

where x is again the feature, xi is the number of instances where the feature of the user personal profile matched the feature of a sample, where the sample is sample of c. The m is the M-Estimator.

Following this, the likelihood is calculated as:

$$likelihood\ (x) = \frac{(1)}{xw} \quad (6)$$

where x is the feature and the xw is the weight of the feature. Note that not all features have the same weight as in the real world some features would weigh more than others. The application has the idea a feature can be part of one of the following group, i.e. price, hobby interests, food and drink interests, and gender. Finally, evidence is calculated as follows.

$$evidence\ (c) = n + m \quad (7)$$

where c is the target class, n is the number of samples belonging to a target class of c, and m as the constant M-Estimator. The formula produces a probability value that is between 0 and 100. This means the application can use the formula for each attraction and put the results into a matrix that holds the attraction ID and the probability. Following this, the matrix is ordered based on the probabilities in a descending order. The application then takes the top n number of attractions, where n is constant setting on the personal recommendations page; for now, it is simply set to three.

4. Implementation and Evaluation

4.1. CF (Item-Based) – Rating

The CF algorithm implemented in this research is illustrated in Algorithm 1.

Algorithm 1 – The CF Algorithm

Collaborative Filtering

Step 0: Given ratings (1-5) by user, average rating of the attraction spot

Step 1: Conduct cosine similarity formula

$$sim(i,j) = \frac{\sum_{u\in U}(R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{u,i} - \bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{u,j} - \bar{R}_u)^2}}$$

Step 2: Conduct the formula for the prediction of user rating

Step 3: Conduct the normalize rating formula:
$normalized_rating = (2*($rating - 1) – (5-1)) / (5-1)

Step 4: Conduct the denormalize formula (scale from 1-5)

Step 5: Return the final denormalized values according to the user's rating:
Displays the outcome after user's rating
Array
[Attraction 1 => 2.932]
[Attraction 3 => 2.900]
[Attraction 6 => 2.832]
[Attraction 7 => 2.807]
*Return the attraction values which are not rated by the users

Under the recommendation list, the system will display all the attraction spots, except for the previously manual rated attraction. According to [12], in item-based recommendation, and based on this context, recommendation is a list of the attractions spots that the user will rate the most. The most important note that must be taken is that the recommendation list must be only on the attractions which are not already rated by the user. Moving forward, there is an array list which consists of the attraction name and the probability values which are on the descending order with the highest to the lowest.

4.2. BF (Naïve Bayes) – User Profile

We provide the CBF algorithm in combination with NBC used in this research as follows.

Algorithm 2 – Content-based Filtering

Content Based Filtering
Step 0: Training data is loaded from the database based on the questionnaire information that given by the user
Step 1: Convert the data (Yes -0 / No-1) into the binary values
Step 2: Store the data into the database
Step 3: Conduct naïve Bayes classifier algorithm
Step 3: **Case** unique ID and attraction ID **OF**
Database:
attraction sample number is incremented by one
Case attraction ID of
Application:
Runs through the interest and likes of sample & personal profile will be incremented one
End Case
Step 4: System will have the list of attraction IDs (number of samples, n)
Step 5: Return each profile interest and matched samples
Step 6: Return the top three attractions which has the highest probability
Outcome:
Attraction 1: 3.55
Attraction 2: 3.49
Attraction 3: 3.45

This recommendation part is based on content-based filtering system. The first and foremost step for a user to get a personalized recommendation is to update their interest form or questionnaire under 'Edit Profile' section. Once it has been updated, the information will be stored into the database so that CBF technique can take place to suggest attractions.

The proposed model has been evaluated using several recommendation data sets, which showed high prediction accuracy rates.

Due to the fact that the intention of the application was to recommend attractions to users based on their personal profile and rating, there were two possible types of applications that could be implemented, a mobile application or a website, with the latter option being selected. Since a web-based application can be accessible using diverse devices, we focus on a web-based recommendation system in this research.

Specifically, the website was implemented using the typical web languages of HTML, CSS, Java script, and PHP. PHP being chosen due to the fact it is cheaper to run a website in PHP on Linux server than a server that can run ASP.NET, although ASP.NET could be a possible alternative.

Before the site could start development, the backing database was first implemented which is used to store data on/about attractions, user logins, user profiles and user reviews. The database is a typical MySQL database that uses SQL to create objects, retrieve and edit data. Each web page of the site has its own PHP file with common functionality being split into functions in a shared file, again which is typical for a website developed in PHP.

In this research, we have discussed how collaborative filtering and content-based filtering work to an extent. This is not only to showcase different types of outcomes of the recommendation algorithms but also to increase model efficiency by employing a machine learning method. In this way, we would be able to fulfil the requirements of more challenging scenarios. Moreover, the evaluation method/algorithm which has been used in both recommendations had been clearly explained. We have also discussed the concerns which need to be addressed such as the security issues. Moreover, it implemented two competitive methods in combination with a NBC algorithm for content-based recommendation.

5. Conclusions and Future Work

In this research, we have implemented item-based collaborative filtering and the content-based filtering, along with the use of a machine learning method, i.e. NBC, for recommendation prediction.

The work could be further improved in a number of ways, although we have optimized the website or system to its maximum. We have observed a few potential drawbacks, e.g. cold start and data sparsity. These issues are the major concerns under any collaborative filtering recommendation system. To address these barriers, we adopted the naive Bayes classier to make recommendation prediction under limited data which shows impressive performance. Also, there is another way to solve the cold start issue is by using dimensionality reduction method. Another method for taking care of the cold start issue is by utilizing dimensionality that expels unrepresentative users and items to reduce the user dimensions [13].

Moreover, in the future, the stated issues can be resolved with the help of hybrid recommender system [14] which will be more efficient compared to other recommender systems. It also has been proven [15] that hybrid recommender system could combine two or more recommendation techniques to obtain more effective results with less complication.

Furthermore, there are a few types of recommender systems under the hybrid technique. A meta-level system is widely used and well-known but however to improve TRS system, a feature combination method should be implemented to improve the respective recommendation system. This is because feature combination can be the engine of hybrid recommender which would be able to merge both collaborative and content-based system. Other machine learning and deep learning algorithms could also be used to further improve the resulting model [16-28]. Optimal model hyper-parameters could also be identified using evolutionary algorithms [29-43].

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